July 2021

Applying Deep Learning in User Equipment Measurable KPIs to Avoid Unnecessary NR RACH Procedures

Gordon Kuo

APPLYING DEEP LEARNING IN USER EQUIPMENT MEASURABLE KPIs TO AVOID UNNECESSARY NR RACH PROCEDURES

Abstract

A user equipment (UE) in a wireless communication network uses a deep learning network model to infer whether a Fifth Generation (5G) New Radio (NR) random-access channel (RACH) failure is likely to occur at a given network location given current Fourth Generation (4G) or 5G measurable key performance indicators (KPIs) at its modem. The KPIs are recorded by the UE as training features during daily usage when NR RACH failure or NR RACH success is detected. The deep learning model is trained based on the recorded features and labels using, for example, supervised learning. The UE implements the trained deep learning network model to infer whether an NR RACH failure is likely to occur based on the features, such as the measurable 4G/5G KPIs, at the current location so that the UE can avoid triggering an NR RACH procedure.

Background

Modems of user equipment (UE) implementing 4G Long-Term Evolution (LTE) and/or 5G NR technology follow the operational procedures defined in the relevant Third Generation Partnership Project (3GPP) specification. The descriptions/procedures provided in the 3GPP specification generally assume the UE does not have a priori information regarding the network on which it camps. As such, if the UE encounters incorrect or non-optimized configurations for a cell within the network, the UE still attempts to connect with the cell according to the procedures defined in the 3GPP specification. In other words, even if the UE has previously encountered incorrect or non-optimized configurations for the cell, the UE is required to try and connect to the cell even though the UE will continue to encounter the issues caused by the incorrect or non-optimized configurations for the cell. For example, an NR cell can be configured and allocated to a UE in a non-standalone (NSA) network. If the UE is too far from the NR cell, the UE cannot establish a link with the allocated NR cell and will experience an NR RACH failure. Under this condition, the UE will operate according to the 3GPP standard and continue to try and connect to the NR cell, resulting in RACH failures. Continuous NR RACH failures result in unnecessary power consumption at the UE and a poor user experience. For example, the user may be presented with a 5G icon on the display of the UE even though 5G service is not available.

As long as the UE follows the procedures defined in the 3GPP specification, avoiding continuous RACH failures when incorrect or non-optimized cell configurations are encountered is difficult. A UE can detect when a continuous NR RACH failure situation occurs and then store an identifier of the LTE anchor cell (i.e., NSA network) at that time. When the UE camps on this LTE cell in the future, the UE can stop NR measurement operations so that NR measurement results are not transmitted to the network, which would trigger a link attempt with the NR cell. However, this method typically prohibits the UE from establishing the NR link even if the UE is close enough to the NR such that a RACH failure would not occur, which causes the UE to lose its NR capability (i.e., act as an LTE-only device).

Description

As described in detail below, a deep learning mechanism is integrated into the modem of a UE to detect and avoid potential NR RACH failures. For example, most users traverse a similar path throughout their daily lives. Therefore, by performing continuous data collection and training of a deep learning network model, the UE is able to predict if an NR RACH procedure will be successful. If the UE determines that the NR RACH procedure will likely be unsuccessful, the

UE is able to make the best decision to avoid the unnecessary NR RACH procedure. Therefore, the UE is able to reduce unnecessary power consumption and enhance the user experience.

One example of a method for detecting and managing potential NR RACH failures using deep learning techniques is shown below in Figure 1. The UE initially obtains training data that will be used to train a deep learning network model for detecting and managing potential NR RACH failures. As the UE travels around the network during daily usage, the UE records various 4G and 5G key performance indicators (KPIs) at the modem(s) of the UE when an NR RACH failure is detected. Examples of these KPIs include the reference signal received power (RSRP) value and reference signal received quality (RSRQ) value of all measurable LTE signals and NR beams; the frequency and cell identifier (ID) of the LTE and NR cells detected by the UE and their RSRP/RSRQ values; the time at which the LTE cells/signals and NR cells/beams were detected; the location of the UE when the LTE cells/signals and NR cells/beams were detected or when a KPI was recorded; the LTE transmission (Tx) power when the LTE cells/signals and NR cells/beams were detected; and so on. The UE records these KPIs as features of the training data and also records the NR RACH failure as a label (e.g., label as “1”) for the training data. If the UE detects that a normal RACH procedure (i.e., no RACH failure) has occurred, the UE records KPIs similar to those described above as features for the training data. The UE also records the NR RACH success as a label (e.g., label as “0”) for the training data.

Based on all the collected training data, the UE trains a deep learning network model using, for example, a supervised learning technique. The recorded KPIs, time, and location can be used as features, and the RACH failure (e.g., “1”) and RACH success (e.g., “0”) indicators can be used as labels to train the deep learning network model. The result of the training process is a trained deep learning network model that takes as input, for example, the measured KPIs and the UE’s current time and location, and infers whether a RACH failure will occur if the UE attempts to connect to a cell at its current location. The deep learning network model can be continuously trained using newly recorded data to improve the deep learning network model's inference. Once the deep learning network model has been trained, the UE implements the deep learning network model to infer whether NR RACH failure is likely to occur at one or more network locations based on the 4G/5G measurable KPIs in the model at those locations. If the inference results indicate that an NR RACH failure is likely to occur, the UE is able to avoid the NR RACH procedure. Otherwise, the NR RACH procedure proceeds as usual.

For example, the UE camps on one LTE (serving) cell (cell A) with frequency = F_LTE_A, Cell ID = CellID_LTE_A, RSRP = RSRP_LTE_A, RSRQ = RSRQ_LTE_A, and current Tx power = TxPower_LTE_A. The UE also detects one LTE neighboring cell (cell B) with frequency = F_LTE_B, Cell ID = CellID_LTE_B, RSRP = RSRP_LTE_B and RSRQ = RSRQ_LTE_B. The UE detects one NR cell (cell X) with frequency = F_NR_X, Cell ID = CellID_NR_X, RSRP = RSRP_NR_X, RSRQ = RSRQ_NR_X. The UE uses (F_LTE_A, CellID_LTE_A, RSRP_LTE_A, RSRQ_LTE_A, TxPower_LTE_A, F_LTE_B, CellID_LTE_B, RSRP_LTE_B , RSRQ_LTE_B, F_NR_X, CellID_NR_X, RSRP_NR_X, RSRQ_NR_X) as the inputs to the trained deep learning model to perform inference operations thereon. If the trained deep learning model provides the inference result "1", which means that UE is likely to experience an NR RACH failure, the UE does not trigger the NR RACH procedure. By not triggering the NR RACH procedure when RACH failure is likely to occur, the UE reduces unnecessary power consumption and provides an improved user experience.

In another example, the UE camps on one LTE (serving) cell (cell C) with frequency = F_LTE_C, Cell ID = CellID_LTE_C, RSRP = RSRP_LTE_C, RSRQ = RSRQ_LTE_C, and current Tx power = TxPower_LTE_C. The UE also detects one LTE neighboring cell (cell D) with frequency = F_LTE_D, Cell ID = CellID_LTE_D, RSRP = RSRP_LTE_D and RSRQ = RSRQ_LTE_D. The UE detects one NR cell (cell Y) with frequency = F_NR_Y, Cell ID = CellID_NR_Y, RSRP = RSRP_NR_Y, RSRQ = RSRQ_NR_Y. The UE uses (F_LTE_C, CellID_LTE_C, RSRP_LTE_C, RSRQ_LTE_C, TxPower_LTE_C, F_LTE_D, CellID_LTE_D, RSRP_LTE_D , RSRQ_LTE_D, F_NR_Y, CellID_NR_Y, RSRP_NR_Y, RSRQ_NR_Y) as the inputs to the trained deep learning model to perform inference operations thereon. If the trained deep learning model provides the inference result “0”, which means that UE is not likely to experience an NR RACH failure, the UE triggers the NR RACH procedure. As such, the various techniques described herein enable the UE to detect and manage potential NR RACH failures. The UE determines not to establish an NR connection only when the UE is at a location that would trigger NR RACH failures compared to disabling its NR capability, even if the UE can establish the NR link. The techniques described herein have the capability of learning, which means that UE can maintain the latest information about the network configurations by updating the trained deep learning model. Also, the network configurations are public and the same for all UEs. Therefore, the training data for one UE can also be useful for other UEs without revealing private information.

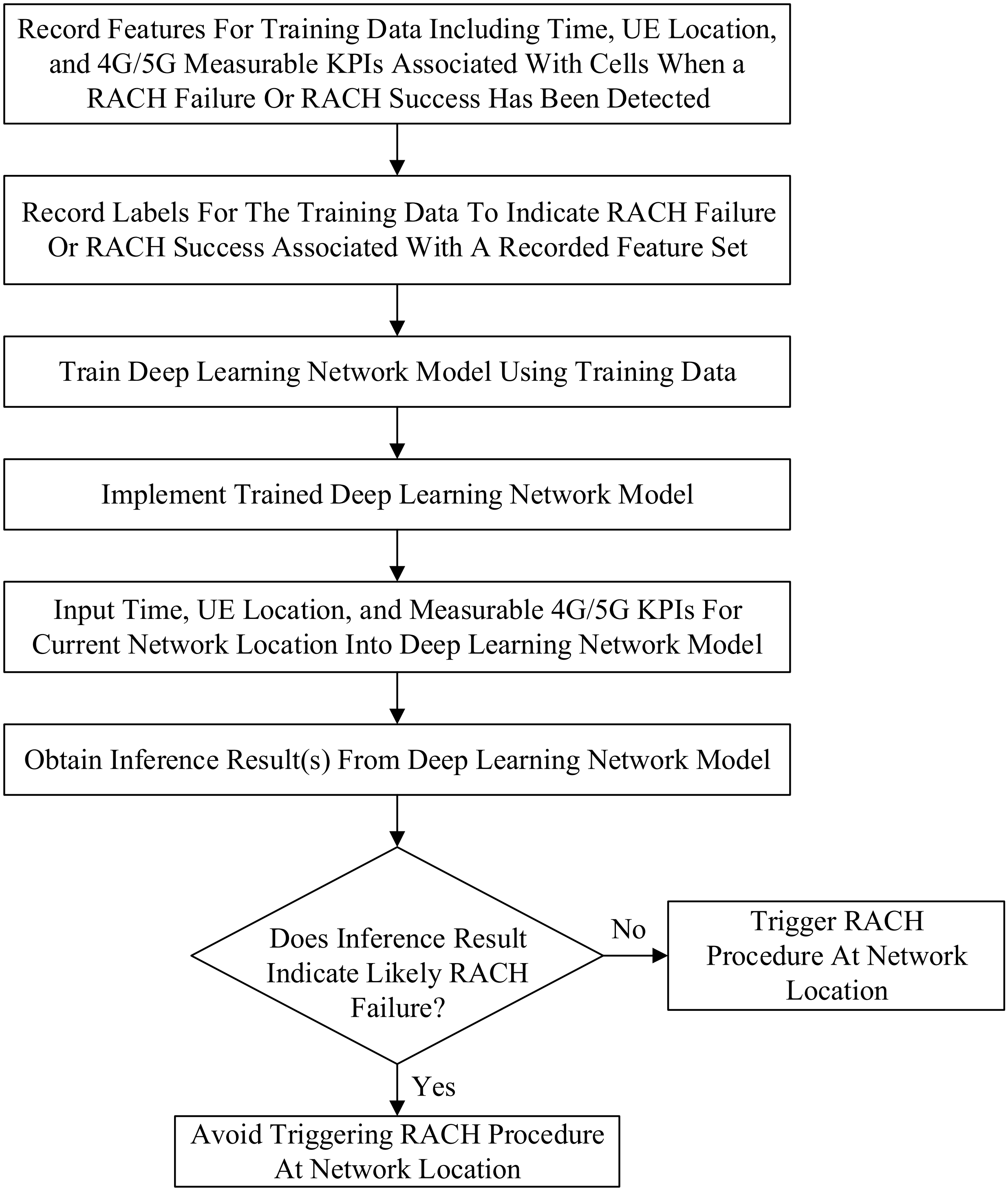
Record Features For Training Data Including Time, UE Location, and 4G/5G Measurable KPIs Associated With Cells When a RACH Failure Or RACH Success Has Been Detected
Record Labels For The Training Data To Indicate RACH Failure Or RACH Success Associated With A Recorded Feature Set
Train Deep Learning Network Model Using Training Data
Implement Trained Deep Learning Network Model
Input Time, UE Location, and Measurable 4G/5G KPIs For Current Network Location Into Deep Learning Network Model
Obtain Inference Result(s) From Deep Learning Network Model
Does Inference Result Indicate Likely RACH Failure?
No
Trigger RACH Procedure At Network Location
Yes
Avoid Triggering RACH Procedure At Network Location

Figure 1

References

1. PCT Patent Application Publication No. 2020/234597, entitled “Random access procedure reporting and improvement for wireless networks”, and filed on May 23, 2019, the entirety of which is incorporated by reference.

2. U.S. Patent Application Publication No. 2020/0045708, entitled “Intelligent Selection Between Singular And Dual Connectivity Method of transmitting and receiving reference signal and apparatus therefor”, and filed on August 2, 2019, the entirety of which is incorporated by reference.

3. U.S. Patent Application Publication No. 2009/0316586, entitled “Method for detecting failures of random access procedures”, and filed on June 17, 2009, the entirety of which is incorporated by reference.

4. U.S. Patent Application Publication No. 2016/0142951, entitled “Data compression techniques for handover and radio link failure recovery”, and filed on June 17, 2009, the entirety of which is incorporated by reference.